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Resilience-based optimal firefighting to prevent domino effect in process plants

Salvatore Cincotta[1,2], Nima Khakzad[2,*], Valerio Cozzani[1], Genserik Reniers[2]

1. Department of Civil, Chemical, Environmental, and Materials Engineering, University of Bologna, Italy
2. Faculty of Technology, Policy, and Management, Delft University of Technology, The Netherlands

* Corresponding author (N. Khakzad) Email: n.khakzadrostami@tudelft.nl
Address: Jaffalaan 5, Delft 2628BX, The Netherlands

Abstract

Domino effects triggered by fire can cause extremely severe damages to the chemical and process plants. In the need of a more effective prevention of fire domino effects, the present study focuses on firefighting which has received less attention compared to passive and active fire protection systems. In the present study, we have introduced a methodology for optimal identification of firefighting strategies so as to increase the resiliency of process plants in dealing with fire escalation scenarios. The area above the resilience curve (AARC), which is equal to the accumulation of loss of resilience over time, was considered as the metric to identify the optimal firefighting strategies. In other words, the strategy leading to the lowest AARC can be selected as the optimal strategy from a resiliency perspective.

Keywords: Firefighting; Domino effect; Resilience; Bayesian network; Optimization.

1. Introduction

In the framework of risk assessment in process plants, the identification of potential accident scenarios is the first step to effectively prevent and mitigate the risk of major accidents. In particular, many of the most tragic industrial accidents that took place in the chemical and process industries take roots in scenarios where a single mishap propagated to nearby units, leading to a chain of events with catastrophic results. This escalation process, which is also known as domino effect, attains the most severe consequences in the ever-growing and complex industrial sites where large numbers of hazardous installations, involving high quantity of dangerous substances, operate within limited separation distances.

Heinrich et al. (1980) states that the occurrence of an accident results from the culmination of a sequence of events, the last one being the accident itself. In Europe, the basic guidelines for preventing major accidents are provided by the Seveso III Directive (Directive 2012/18/EU). The term domino effect is used in the context of industrial establishments or groups of establishments where the consequences of a primary event (fire or explosion) may increase because of the proximity of adjacent hazardous units (i.e., those containing flammable/explosive materials) and thus the escalation of the primary event to secondary and tertiary events, and so on. Domino effects triggered by fire are amongst the most frequent and feared accidents in the chemical and process plants (Browning and Searson, 1989).

To reduce the escalation of primary event scenarios, a number of preventing and protective measures can be implemented depending on the available resources, the type of installations, and potential fire scenarios. Clearly enough, some of these measures can prove ineffective in preventing further escalations due to malfunction, exposure to severe heat, or inadequate capacity. In the case of fire scenarios this probability depends on the primary accident but also on factors like the proximity of potential secondary units. As such, firefighting plays a key role in controlling and delaying fire escalation in process plants.

Effectiveness of firefighting strategies is highly dependent on time. For instance, considering the cooling strategy of units exposed to heat, time is needed for the shell temperature to drop under the failure threshold, which can delay but not completely exclude the failure of equipment. Also, time is needed for mobile resources to reach the endangered installations and start the intervention. Not all the possible scenarios can trigger a plausible escalation. Indeed, the severity of the secondary scenario should exceed the consequences of the primary event to talk about a true "escalation" as intended to be a domino effect by the Seveso III Directive (2012).

Conventional models fail in analysing accidents in complex sociotechnical systems caused by contemporary or concomitant factors in conjunction with the dynamicity of the working environment that are apparently unrelated or either unexpected to happen. These flaws can be overcome by accepting a systemic view of safety deeply connected with the precepts of resilience engineering.

The first analysis of the resilience engineering concepts was carried out by Hollnagel (2011) where resilience is defined as "the ability that makes a system both safe and efficient, allowing it to maintain and recover a dynamic state of equilibrium while keeping functioning after a mishap or under permanent stress". By accepting this natural variability, the focus shifts towards proactively finding which interdependent factors and mutual interactions can cause any escalation in the view of creating more flexible and thus resilient processes. Indeed, resilience engineering is interested in understanding how to enhance a system's ability to recognise, adapt and absorb variations, disturbances and disruptions in order to effectively react and quickly return to a safe functioning state.

In anticipating the potential upcoming mishaps, resilience is not only concerned with the ability of recomposing the damaged parts of the systems, but also with understanding the chances of adaptability they possess and the availability and the range of sources to perform such behaviour. There have been some interesting works to take into account the concept of resilience in the safety of process facilities. Defining the resilience as the ability to properly recover quickly after an upset, Dinh et al. (2012) demonstrated how to evaluate the resilience of a safe design of a process operation. Knegtering and Pasman (2009) expressed the need of changing the process safety administrations including the resilience concepts, continuous learning from experience and proposing a holistic approach for new safety management. An extensive review of the definitions and assessments of resilience is provided by Hosseini et al. (2016).

In the field of engineering, the concept of resilience is relatively new and its definition strongly depends on the characteristics of the system of interest. The present study is aimed at developing a resilience metric to identify optimal firefighting intervention strategies to effectively suppress the propagation of fire across process plants. To this end, we first define a resilience metric to investigate the efficiency of firefighting strategies, and then employ a conventional Bayesian Network (BN) approach to model fire escalation probabilities with and without firefighting intervention. However, since the resilience is a time dependent metric, the time it takes for the fire to spread from one unit to the other(s) as well as the delay time of firefighters (arrival time plus the deployment time) are taken into account in the calculation of the resilience metric. Section 2 recapitulates the basic of BN and how it can be used to model domino effects caused by fire. Section 3 is devoted to the development of a resiliency metric in the context of emergency firefighting. In Section 4, the methodology is applied to an illustrative case study, while the work is concluded in Section 5.

2. Fire escalation modelling using Bayesian network

2.1. Bayesian network

BN is a graphical representation of uncertain knowledge that conveys the information on correlation between variables via conditional probabilities tables (Pearl, 1988). BNs are acyclic graphs in which the variables that are the subject of inquiry are represented through nodes and their conditional probabilistic dependencies are represented with direct arcs that connect the nodes. Each node is associated with a probability function that takes, as input, a particular set of values for the node's parent variables, and gives as output the probability (or probability distribution, if applicable) of the variable represented by the node. This means that the information flows across the graph from the parent nodes down to the child nodes.

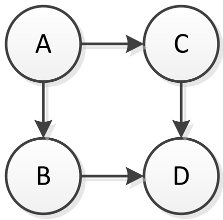

Fig. 1. A typical Bayesian network

Quite often, the values that represent the possible states for a node are Boolean variables. Also in a BN, given its parent nodes, a node is conditionally independent of its non-descendant nodes. As such, the joint probability distribution of a set of variables X ={x_1, x_2, …,x_n} can be written as:

$$P(x_1, x_2, \dots, x_n) = \prod_{i=1}^{n} P(x_i|\pi_i) \qquad (1)$$

where π_i is the parent sets of variable x_i. According to the BN in Fig.1, the joint probability distribution of the nodes is equal to:

$$P(A, B, C, D) = P(A)P(B|A)P(C|A)P(D|B, C) \qquad (2)$$

Having the joint probability distribution of the variables, marginalization can be employed to obtain the probability of each variable (Fenton and Neil, 2013). BNs are increasingly used in the construction and simulation of complex systems where the presence of interdependent factors and hidden variables make the application of other probabilistic techniques very challenging if not impossible.

2.2. Domino effects triggered by fire

In an industrial set up, the domino effect is formed when an initiating event such as fire or explosion spreads from an industrial unit or equipment to another, resulting in the damage of one or more secondary targets within the same plant (internal domino) or nearby plants (external domino). The characterization of a domino effect includes the identification of possible primary events, escalation and subsequent propagation of primary events, and identification of secondary and higher order events.

Considering the risk assessment of domino effect accidents, Cozzani at al. (2005) developed a systematic procedure, evaluating the most credible combination of events, their likelihood of occurrence and the minimum required safety distance among the potential targets. For fire domino effects, the procedural and normative measures are quite often aimed at limiting the dangerous effects via fireproofing coatings and automatic protection devices on the most critical units (Tugnoli et al., 2012; Khakzad et al., 2018).

In suppressing and confining possible escalation of fires, the intervention actions must act in order to break the vicious cycle that aliments the escalations. The tactical decision for fire suppression differentiates mainly in confinement, ventilation and exposure protection (Svensson, 2002). The approaches that are suggested in the literature allow for straightforward estimation of indices or escalation vectors and thresholds that provide usual information on the recognition of potential hazards and the risk assessment. It is important to underline how the methodologies cover the aspects of fire prevention in the phase of process design and plant layout as proactive measures as well as fire protection of the critical units as reactive measures.

Khakzad et al. (2013) developed a methodology based on BN to model domino effect in process plants. In their approach, probit models were used to calculate the conditional probabilities of the BN. Then through the comparison with threshold values, potential secondary units were selected and the domino probability was assessed as the product of the probability of the primary event and the probability of escalation.

The fire initiation, fire propagation, and fire control at a process plant can be considered as the disruption, vulnerability, and the recovery phases characterizing a resilient firefighting strategy. BN can be employed to analyse all the foregoing phases during fire domino effects due to its flexibility in modelling different escalation scenarios and evaluating respective probabilities under uncertainty. The present study is aimed at defining a resilience metric so that optimal firefighting strategies can be determined based on which.

3. Resilience metric for firefighting

3.1. Definition of resilience and its components

Resilience is a broadly employed concept and can hardly be described univocally. The variability of the threatening situations offers different expected and unexpected scenarios to which the system should respond. In general, resilience can be described as the ability of a system to accustom its functionality in the midst of the disturbance actions and ultimately manage to steer its performance back to acceptable levels. The main point of resilience-based assessment methods is to define resilience metrics to evaluate the performance of systems. These metrics can be characterized as (Hosseini et al., 2016):

- Deterministic vs. Probabilistic, where the former excludes stochastic uncertainty, and
- Dynamic vs. Static, where the former includes time-dependent behaviours.

The resilience capacities that the metric should be able to address include (Hosseini et al., 2016):

- Absorptive capacity, that is, the extent to which the system can easily absorb the perturbations and thus minimize the impacts. Since it is a characteristic of the system, it roots in the original design phase and more specifically in the robustness (preventing measures) and redundancy (allowing different alternatives).
- Adaptive capacity, that is, the system ability to organize and readjust its functioning according to the perturbations. It roots in the organizational phase and more specifically in how bypass operations (resourcefulness) are dynamically carried out in the face of perturbations.
- Restorative capacity, that is the ability of a system to repair itself. This reparation must be effective and fast enough to not allow a further system decay. The new stable state might allow the system to enhance the absorptive capacity by learning from the experience.

Woods (2007) defines resilience as the capability of a system to handle disruptions and variations that fall outside the adapting mechanisms defined during the design phase. When a system is conceptualized and the safety constraints are applied, the envelope of the accepted and sustained variability is also traced. A good resilience practice is concerned with monitoring the operations that drift near the boundaries and possibly helps the system better accommodate ever-changing events.

3.2 Application of resilience engineering to industrial safety

In the process industry, the advancement of the resilience-based approaches has been limited, mainly due to the tendency to rely on well-assessed methodologies and the lack of clarity of the conceptual links between the resilience concepts and the practical procedures. One of the first attempts to fill the gap in assessing resilience was carried out by Shirali et al. (2013) who assessed resilience from a safety culture perspective in a process plant. The tools used to perform such task were in the form of questionnaires filled in by employees in the front-line of production and allowed to find a number of resilience indicators to identify the most critical process units.

Holistic approaches are also introduced in the study of resilience to manage process safety risks (Pasman et al., 2013). The idea of extending resilience into safety science has also been proposed by Steen and Aven (2011). The new insight considers that the main component of risk is uncertainty, and probability is a knowledge based tool to express uncertainty in assessing threats and their consequences. A statistical based resilience evaluation framework was successfully obtained analysing accidents and near-misses in an existing process plant and quantifying the key contributing resilience parameter (Palazzi et al., 2014).

A resilient engineering model was also adapted by Hansson and Herrera (2009) to reduce occupational injuries in the oil and gas industry. The main question is how the high reputation on safety of such industries can match the increasing number of injuries, and if resilience engineering can be used to reduce this trend. Whitson and Ramirez-Marquez (2009) related the network resilience to the time to restore the performance in the case of external damaging events due to components failure. Using reliability concepts and Monte Carlo simulations, the resilience metric is evaluated as a probability density function by which a specific scenario would not be able to perturb the network integrity.

Reliability was also used in a recent work by Yodo and Wang (2016) with a focus on the early stages of the design of complex engineering systems. In other words, resilience is measured as the ability to prevent and mitigate accidental scenarios that affect the safety integrity. A lack of resilience results in the inability to confront sudden and unforeseen disturbances; further, organisation policies that do not support a constant improvement in safety are also responsible for an erosive drift and higher complacency.

As mentioned before, different views on what characteristics to highlight can lead to different definitions of resilience. In the basic meaning, resilience is the ratio of the recovery at generic time to the losses suffered by the system up to that point in time. Given a general system, it first dwells on the original state before a disruptive event triggers the transition to a disrupted state (Henry and Ramirez-Marquez, 2012) (Fig.2).

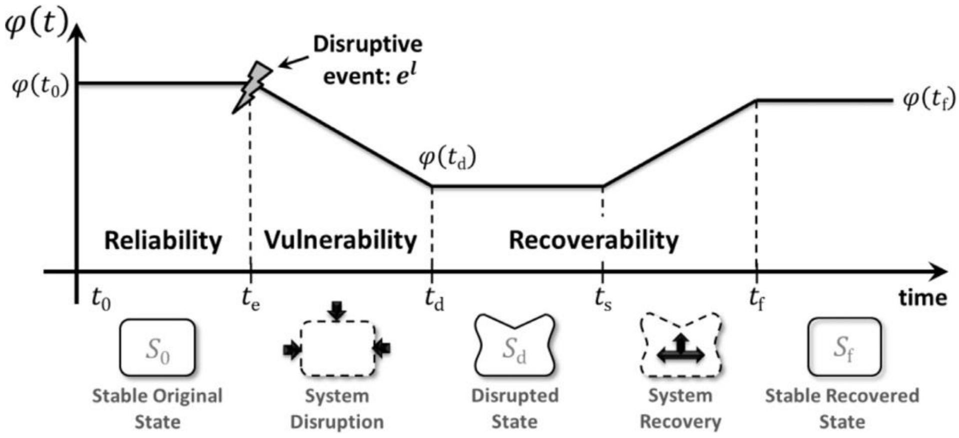

Fig. 2. System performance change over time (Henry and Ramirez-Marquez, 2012)

Subsequently the system can recover thanks to a resilient action and bounce back to a recovered state that could be different from the original one. This means that after the disruptive action, identified with e^l in Fig. 2, the system can act resiliently based on the effects this event has on the formerly assumed perfect performance on the time necessary for the effective recovery and on the cost derived from the application of the recovery measures. Resilience can be described as the proportion of service restored through recovery actions following a primary disruption e^l. As such, resilience Я can be modelled as Equation (3):

$$Я\left(t\middle|e^j\right) = \frac{\varphi(t|e^l) - \varphi(t_d|e^l)}{\varphi(t_0) - \varphi(t_d|e^l)} \quad (3)$$

where $Я\left(t\middle|e^l\right)$ is the resilience at time t; $\varphi\left(t\middle|e^l\right)$ is the system's performance at time t; $\varphi(t_d|e^l)$ is the system's lowest performance, and $\varphi(t_0)$ is the system's performance before the disruptive event e^l occurs. Using the same metric, Baroud et al. (2014) investigated the resilience of waterway networks. Considering the metric in Equation (3) as one of the most comprehensive and suitable resilience metrics in engineering systems, we present a slightly modified metric in the next section to be applicable to firefighting during domino effect scenarios.

4. Resilience metric in the context of firefighting

Considering the concepts presented in Section 3 and bearing in mind the aspects of resilience engineering in process plants, the main focus of the present study is on the vulnerability phase (fire escalation zone in Fig.3) and the recovery phase (firefighting zone in Fig.3) in the case of fire scenarios. In other words, the process plant's vulnerability to a primary fire (disruption) can be modelled as the susceptibility of the plant to the fire spread whereas the plant's recoverability can be modelled as the effectiveness of firefighting in controlling and delaying the fire spread.

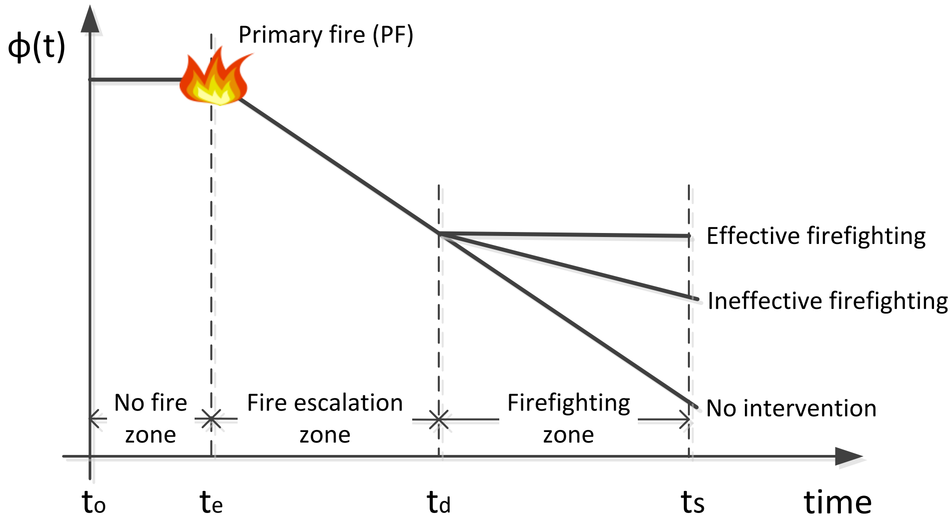

Fig. 3. Performance of a process plant during fire escalation

The disrupting event, i.e., the primary fire (PF), occurs at t_e when the performance of the system (the process plant) is considered at its peak. The performance of the system drops accordingly, and the system enters the so-called fire escalation phase. For a time span from t_e to t_d, the performance keeps dropping according to the uncertainty related to the spread of the primary fire to the other units although the slope of the declining trend can be mitigated if effective fire protection actions are in place. The extension of the fire escalation zone implies a free propagation of fire without the intervention of the firefighters.

If the firefighters manage to arrive in time (i.e., before the time to failure of exposed storage tanks), they are assumed to be able to extinguish the primary fire before it finds a chance to spread to the other tanks (i.e., no fire escalation zone). Otherwise, the longer the firefighters delay arrive, the wider the escalation zone, and the larger the process plant's performance loss. The time t_d indicates the moment when the firefighters intervene and start suppressing the fire.

If the resources are enough and the deployed intervention is able to control the spread of the fire, the performance of the system reaches a stable state (Effective firefighting in Fig. 3). Otherwise, if the intervention is ineffective and allows the partial spread of fire to secondary units, the performance keeps dropping and eventually reaches a constant minimum value (Ineffective firefighting in Fig. 3). The time indicated with t_s represents the furthest time for possible escalations. If the firefighters are present on site at the time of the primary fire, no escalation phase would be assumed. In this regards, if the intervention action is immediate and successful, the performance drop is limited to that of the primary event. Late arrival of the firefighters can increase the decline of the performance leading to states in which no intervention can prevent escalations and save the plant. It should be noted that Fig. 3 does not depict the time devoted to the replacement or repair of the damaged units. Otherwise, Fig. 3 could have been extended to t_f as in Fig. 2. In that case, based on the number of replacements or the quality of repair (e.g., as good as new), the performance could be restored to its original value before the primary fire occurred.

That being said, the goal of an effective and optimal firefighting would be to identify the intervention strategies which ideally prevent or at least delay the spread of fire to reduce the loss of performance to the lowest. The resilience metric scores differently according to which intervention strategy is considered in the analysis. Clearly, the optimal firefighting strategy is the one that prevents the spread of fire to the neighbouring units within a short intervention time. In the light of the definition of resilience and considering the nature of the application case, the metric expressed in Equation (3) can slightly be modified as:

$$Я(t|PF) = \frac{\varphi(t|PF) - \varphi(t_d^*|PF)}{\varphi(t_0) - \varphi(t_d^*|PF)} \quad (4)$$

where PF is the primary fire, and t_d* is the expected time of fire escalation to all the units in the absence of firefighting intervention. In that case, the performance reaches the minimum value and the resilience score goes to zero.

Given an intervention strategy, the numerator represents the difference between the value of the performance at a generic time t ∈ (t_0, t_s) and the performance in the case of no firefighting intervention at t_d*. The imposed condition of t_d* derives from the assumption that any deployed intervention strategy, regardless of its effectiveness, would lead to a performance value higher than the worst case scenario. The denominator represents the maximum possible loss of performance, i.e., the difference between the original state and the worst case scenario. The resilience metric scores zero only in the case of ineffective intervention strategy, that is, when t assumes the value of t_d*. The metric scores one, when t coincides with t_o, i.e. when the value of expected resilience is the maximum. The resilience metric encompasses the dynamic evolution of the performance and the uncertainty in the efficiency of firefighting strategies.

The performance function in Equation (4) is defined as:

$$\varphi(t|PF) = \frac{n(t)}{N} = \frac{N - \sum_{i=1}^{N} P(i|PF,t)}{N} \quad (5)$$

where N is the total number of units in the plant; n(t) is the number of intact units at time t (the units still not involved in the fire escalation); $P(i|PF,t)$ is the probability of the i-th unit getting involved in the domino effect at time t. The performance index depends on the state of the system at time t and is a function of the number of units that given the firefighting strategy can be kept safe. Indeed, the numerator represents, at a specific time t, the number of intact units as the difference between the total number of units of the plant and the sum of the conditional probabilities of fire escalation to the secondary units by time t. The denominator represents the total number of tanks. The performance assumes different values at different times as more units may get involved in the domino effect.

The performance evaluation is hence a discrete process which allows to associate a numeric value to the resilience metric only at the times when an escalation scenario takes place. Slowly reacting systems in damage-enhancing environments perform worse in terms of resilience than their fast responsive counterparts. In the first case, the firefighters need to deploy the intervention strategy for a long time under dangerous conditions, increasing the probability of casualties; besides, the amount of water required for exposure protection can easily exceed that necessary for the extinction of fire. Moreover, the later the fire is completely suppressed and the recovery phase can take place, the higher the economic loss for the facility.

Therefore, if the performance and resilience loss are converted into continuous processes by means of the polynomial interpolation of the discrete points, the Area Above the Resilience Curve (AARC) represents mathematically the loss of resilience for the corresponding time interval. The larger the AARC, the larger the resilience loss over time and thus the less effective the deployed firefighting strategy. The use of AARC is not new since it has already been practiced in earthquake restoration (Bruneau et al., 2003) and organizational and business management (Sahebjamnia et al., 2015). The comparison of the AARC values obtained for different intervention strategies allows to identify the optimal firefighting approach as the one with the least performance loss in the shortest time.

5. Optimal firefighting under insufficient resources

5.1. Case study

A hypothetical fuel storage plant in Fig. 4 is used to demonstrate the application of the proposed resilience metric and its role in the identification of optimal firefighting strategies. The plant consists of eight identical atmospheric storage tanks of gasoline with a diameter of 20 m, height of 6.5 m, and volume of 2000 m^3. The centre-to-centre distance between the tanks are presented in Table 1.

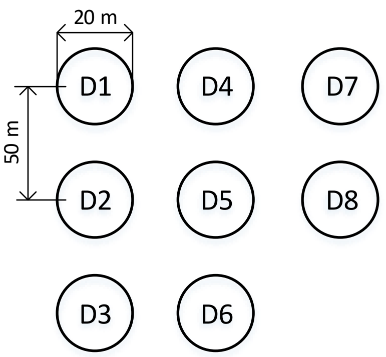

Fig. 4. An illustrative fuel storage plant (Khakzad et al., 2013)

Table 1. Center-to-center distance (m) from unit Di to Dj (Khakzad et al., 2013)

Di↓ Dj→	D1	D2	D3	D4	D5	D6	D7	D8
D1	-	50	100	50	71	112	100	112
D2	50	-	50	71	50	71	112	100
D3	100	50	-	112	71	50	142	112
D4	50	71	112	-	50	100	50	71
D5	71	50	71	50	-	50	71	50

D6		112	71	50	100	50	-	112	71
D7		100	112	142	50	71	112	-	50
D8		112	100	112	71	50	71	50	-

Considering tank fires as the likeliest fire scenarios, the amount of heat radiation tank Dj received from a tank fire at Di has been calculated and presented in Table 2 using software ALOHA (2014) given a wind speed of 2 m/s from north.

Table 2. Heat radiation Qij (kW/m^2) from unit Di to Dj (Khakzad et al., 2013)

Di↓	Dj→	D1	D2	D3	D4	D5	D6	D7	D8
D1		-	19.3	4.6	19.3	9.3	3.6	4.6	3.6
D2		19.3	-	19.3	9.3	19.3	9.3	3.6	4.6
D3		4.6	19.3	-	3.6	9.3	19.3	2.2	3.6
D4		19.3	9.3	3.6	-	19.3	4.6	19.3	9.3
D5		9.3	19.3	9.3	19.3	-	19.3	9.3	19.3
D6		3.6	9.3	19.3	4.6	19.3	-	3.6	9.3
D7		4.6	3.6	2.2	19.3	9.3	3.6	-	19.3
D8		3.6	4.6	3.6	9.3	19.3	9.3	19.3	-

Having the heat radiation amounts, probit functions (Landucci et al., 2009) can be used to calculate the fire escalation probability from a burning tank to an exposed tank:

$$\ln(ttf) = -1.13 \ln(Q) - 2.67 \times 10^{-5}\, V + 9.9 \quad (6)$$

$$Y = 9.25 - 1.85 \ln\left(\frac{ttf}{60}\right) \quad (7)$$

$$P = \Phi(Y - 5) \quad (8)$$

where ttf is the time to failure (s) of an exposed tank, Q is the heat radiation (kW/m^2) the exposed tank receives from an adjacent tank fire, V is the volume (m^3) of the exposed tank, Y is the probit value, Φ(.) is the cumulative density function of standard normal distribution, and P is the escalation probability of fire to the exposed tank. As suggested by Cozzani et al. (2005), a threshold heat intensity of 15 kW/m^2 would be needed for fire escalation to an exposed atmospheric tank. For instance, as can be noted from the values in Table 2, a tank fire at D1 cannot cause damage and thus escalate to D5 ($Q_{15} = 9.3 < 15$ kW/m^2). However, if both D1 and D3 are on fire, due to the synergistic effects, the fire may escalate to D5 since $Q_{15} + Q_{35} = 9.3 + 9.3 > 15$ kW/m^2.

Having the heat radiation intensities in Table 2, the fire domino effects given a primary fire can be modelled using the BN methodology developed by Khakzad et al. (2013). Fig. 5 depicts the BN for modelling fire escalation in the fuel storage plant given a tank fire at D4.

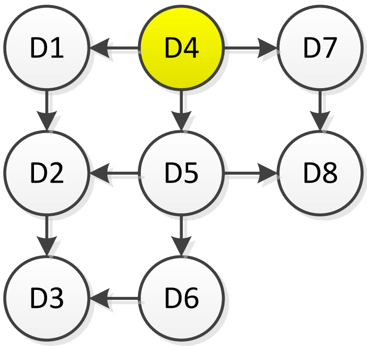

Fig. 5. BN for fire escalation modelling given a primary tank fire at D4.

The root node of the BN is represented by D4, where the primary fire takes place. The arcs from D4 to D1, D5, and D7 are because these tanks receive a heat radiation higher than the predefined threshold of 15 kW/m^2. Identifying these tanks as the secondary units involved in the domino effect, D2, D6, and D8 can be selected as the tertiary units and D3 as the quaternary unit. The conditional probability table (CPT) of D2 is shown in Table 3 in which the probabilities have been calculated using Equations (6)-(8) and considering the synergistic effects of D1 and D5 on D2.

Table 3. Conditional probability table of D2

D1	Fire		No Fire	
D5	Fire	No Fire	Fire	No Fire
Fire	0.89	0.43	0.43	0.00
No Fire	0.11	0.57	0.57	1.00

Assigning the CPTs to all the nodes in Fig. 5, the escalation probabilities of the tanks can be calculated by implementing the BN in the software GeNIe (2014). For illustrative purposes, we will consider two fire cases:

- Case 1: a primary tank fire at D4 with no further escalation, and
- Case 2: a primary tank fire at D4 which escalates to D1, D5 and D7.

To model possible fire domino effects under the influence of firefighting strategies, two more assumptions are made in the present study:

- Due to the limited resources, the firefighters can only cool two storage tanks at a time.
- The probability of fire escalation to the cooled tanks would be zero. This can be done by instantiating the state of a cooled tank to “No fire” in the corresponding BN.

The foregoing assumptions imply that given a primary tank fire, if the firefighters arrive and start cooling an exposed tank before the tank’s original ttf, the tank would be saved.

5.2. Firefighting scenarios

5.2.1. Case 1: Primary fire at D4 with no escalation

The first case to study is when the firefighters are present on site at the time of a primary tank fire at D4 and immediately start to control the fire escalation. In this regard, the firefighters' aim would be to identify the optimal pair of exposed tanks to cool to minimize the probability of fire spread and thus to minimize the performance loss.

In order to evaluate the resilience metric of the potential strategies, the worst case scenario is here addressed as the 'Fire All', that is, the escalation of fire to all the tanks without intervention of firefighters. The time evolution of the process is exemplified in Table 4, where for each unit the number is equal to the escalation probability (calculated using the developed BN); the number 0 stands for an intact state.

The time t_e, i.e., the time when the primary event occurs, is considered to be at zero. The secondary units D1, D5 and D7 receive a heat radiation of 19.3 kW/m^2 from D4. The ttfs of theses secondary units can be calculated using Equation (6) as 10.95 min. This means that after t_1 = 10.95 min, with the assumption of no intervention, these three units would catch on fire as the secondary units with a probability of 0.43. Subsequently, D2 and D8 would be exposed to a total heat radiation of 38.6 kW/m^2 due to the synergistic effects of the secondary units. Using Equation (6), the ttf of D2 and D8 would be calculated as 5 min, and therefore it would take the fire t_2 = 10.95 + 5 = 15.95 min to spread to D2 and D8 with a probability of 0.38. As time passes more units get involved in the chain of fires, generating an escalation which would affect the entire plant in 26.9 min after the start of the primary fire at D4, with D3 as the last unit.

Table 4. Escalation probabilities over time for "Fire All".

	t_0	t_e	t_1=10.95	t_2=15.95	t_3=21.9	t_4=t_d^*=26.9
D4	0	1	1	1	1	1
D1	0	0	0.43	0.43	0.43	0.43
D5	0	0	0.43	0.43	0.43	0.43
D7	0	0	0.43	0.43	0.43	0.43
D2	0	0	0	0.38	0.38	0.38
D6	0	0	0	0	0.18	0.18
D8	0	0	0	0.38	0.38	0.38
D3	0	0	0	0	0	0.24

Having the escalation probabilities in Table 4, the values of the performance and the resilience can be calculated using Equations (5) and (4), respectively, as in Table 5. For instance, the performance and resilience metric at t_1 can be calculated as $\varphi(t_1|D4) = \frac{n(t)}{N} = \frac{8-1-(3\times0.43)}{8} = 0.714$, and $Я(t_1|D4) = \frac{\varphi(t_1|D4)-\varphi(t_d^*|D4)}{\varphi(t_0)-\varphi(t_d^*|D4)} = \frac{0.714-0.566}{1-0.566} = 0.341$. The patterns of the performance and the resilience indicators are shown in Figures 6 and 7, respectively.

Table 5. Performance and Resilience metric for “Fire All” in Case 1.

	$t_0 = -\infty$	$t_e = 0$	$t_1 = 10.95$	$t_2 = 15.95$	$t_3 = 21.9$	$t_4 = t_d^* = 26.9$
φ	1	0.875	0.714	0.619	0.596	0.566
R	1	0.712	0.341	0.122	0.069	0

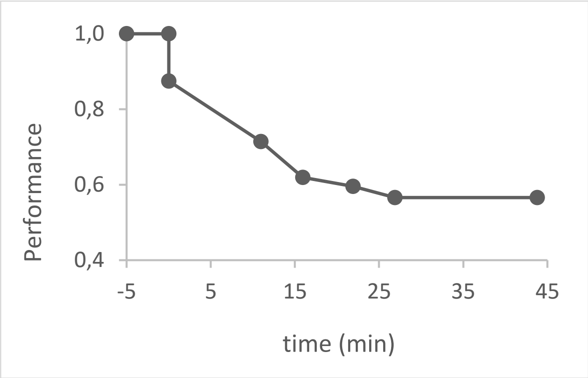

Fig. 6. The fuel storage plant’s performance in case of “Fire All” given a tank fire at D4.

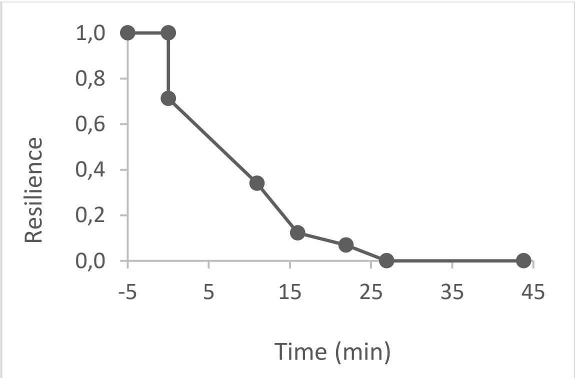

Fig. 7. The fuel storage plant’s resilience in case of “Fire All” given a tank fire at D4.

The graphs have been extended until t = 45 min to be able to make a comparison among different strategies in some of which it would take about 45 min (43.8) for the fire to escalate across the entire plant (t_s). The same procedure for the calculation of the performance and resiliency can be followed for different firefighting strategies. The results of resilience metrics for some firefighting strategies are shown in Fig.8 where S_{ij} refers to the cooling of Di and Dj.

The comparison of the resiliency metrics may not clearly demonstrate the relative efficiency of the respective firefighting strategies. For instance, as can be seen from Fig. 8, for the first 33 min, the plant’s resiliency resulting from S12 is lower than that of S58, but the resiliency resulting from S58 becomes lower afterwards. The AARC is an index that may better describe the loss of resilience over time for different firefighting strategies: the larger the AARC the more the loss of resiliency over time and thus the less effective the firefighting strategy. In Fig. 9, the AARC values of the firefighting strategies have been presented where S15 is associated with the smallest AARC and thus can be selected as the optimal firefighting strategy.

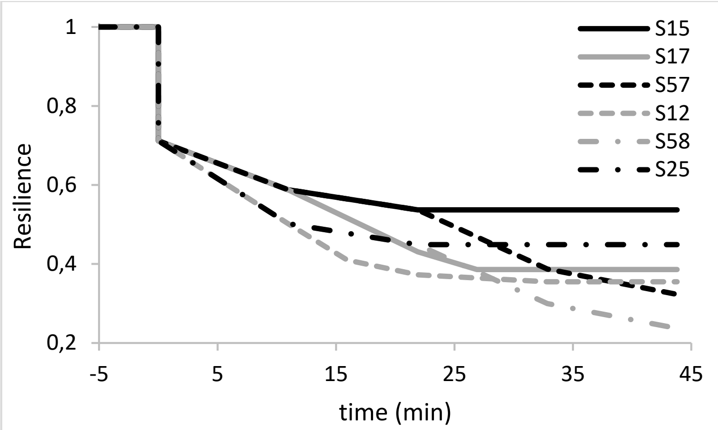

Fig. 8. Comparison of the resiliency of some selected firefighting strategies (Case 1).

It is also worth noting that the AARC of S17 is slightly greater than that of S25 (23 vs. 22.5), suggesting the latter as a relatively more effective strategy. This observation is interesting because S17 would intuitively be perceived as a better option than S25 as both D1 and D7 are the secondary units and directly impinged by the heat radiation of D4 compared to D5 and D2 which are a combination of secondary and tertiary units.

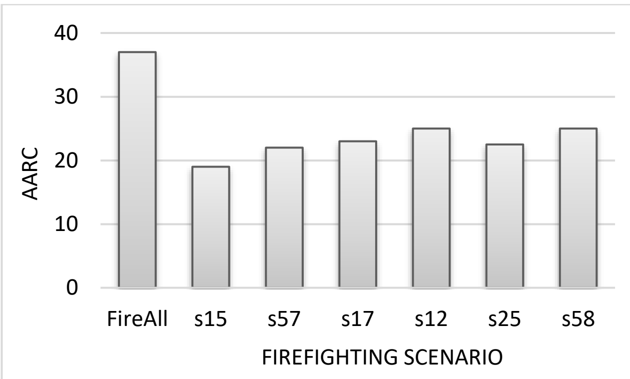

Fig. 9. Comparison of AARC of some selected firefighting strategies (Case 1)

5.2.2. Case 2: Primary fire at D4 escalates to D1, D5 and D7

In this case, the analysis focuses on the condition where the firefighters arrive between 10.95 min and 15.95 min from the start of fire at D4. If the firefighters arrive in the aforementioned time interval, the fire would have already spread to D1, D5 and D7 (ttf of these three tanks is 10.95 min). If the firefighters arrive later than 15.95 min, the fire would have spread, with a given probability, to D2, and D6 as well. The calculated values of the performance and the resilience for “Fire All” are presented in Table 6.

Table 6. Performance and Resilience metric for “Fire All” in Case 2.

	$t_0 = -\infty$	$t_e = 0$	$t_1 = 15.95$	$t_2 = 21.9$	$t_3 = 26.9$
φ	1	0.748	0.671	0.653	0.628
R	1	0.323	0.116	0.067	0

Following the same approach as the previous section, the change of resilience metric with time and the AARC for some selected firefighting strategies have been depicted in Figures 10 and 11, respectively. As can be seen from Fig. 11, the firefighting strategy S28, i.e., cooling of D2 and D8, is associated with the lowest AARC and can thus be identified as the optimal strategy.

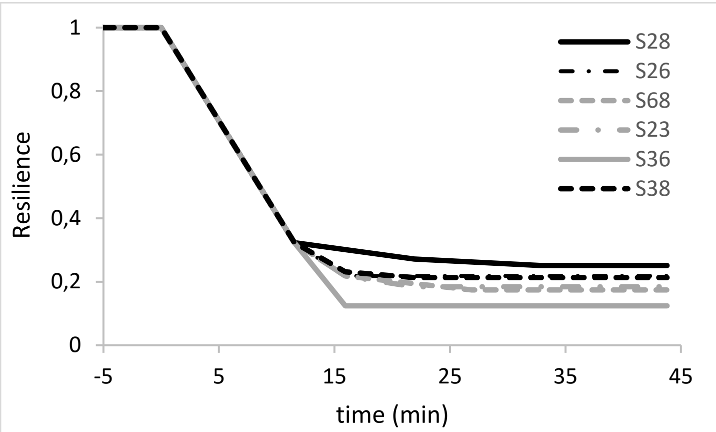

Fig. 10. Comparison of the resiliency of some selected firefighting strategies (Case 2).

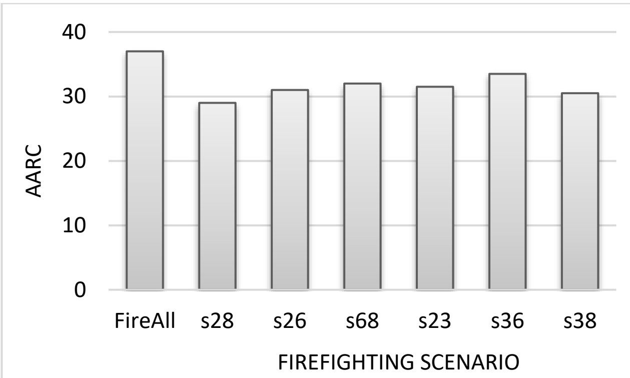

Fig. 11. Comparison of AARC of some selected firefighting strategies (Case 2).

The results of Case 2 are worthwhile because at the first glance, S26, i.e., cooling D2 and D6, may seem more intuitive. This way, the fire would have been escalated from D5 to D8 but at least D2, D6, and D3 could have been saved. However, with a closer look at the heat radiation intensities in Table 2, it can be noted that the fire escalation chain (D2 ← D5 → D8) is more likely and also takes less time than the fire escalation chain (D5 → D6 → D3). This is why the cooling of D2 and D8 takes priority, from a resilience perspective, over D2 and D6, as it can reduce the probability of fire escalation and also buys more time for providing more firefighting resources. This outcome demonstrates the efficacy of the developed methodology in the sense that not all the seemingly intuitive firefighting strategies would be optimal.

6. Conclusions

In the present study, an attempt was made to develop a methodology for the identification of optimal firefighting strategies for control and suppression of fire domino effects in process plants. To this end, we proposed an innovative resiliency metric and employed it in conjunction with a Bayesian network methodology for modelling domino effects with and without firefighting intervention. The methodology was shown to be able to increase both the absorptive and recoverability capacities of process plants in withstanding fire escalation scenarios.

The use of the Area Above the Resilience Curve (AARC) was proposed in the present study as an effective discriminating factor to rank the firefighting strategies as it facilitates combining the loss of resiliency and the time needed for firefighting. In this regard, further advancements can be carried out by considering more factors such as the availability and reliability of passive and active fire protection systems, human resources, and the available budget for additional intervention. Further, the application of inherently dynamic techniques such as dynamic Bayesian network is expected to better capture the spatial-temporal changes of resiliency. This will be the scope of our future study.

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